A Data and Model Visualization System for Android Malware Detection

CPSC 547

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- Cybercriminals target mobile due to large user base
- Rely on machine learning

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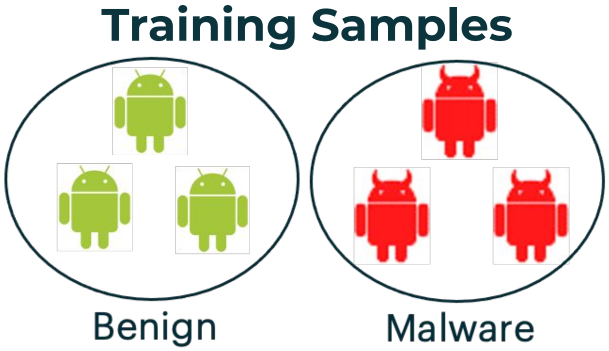

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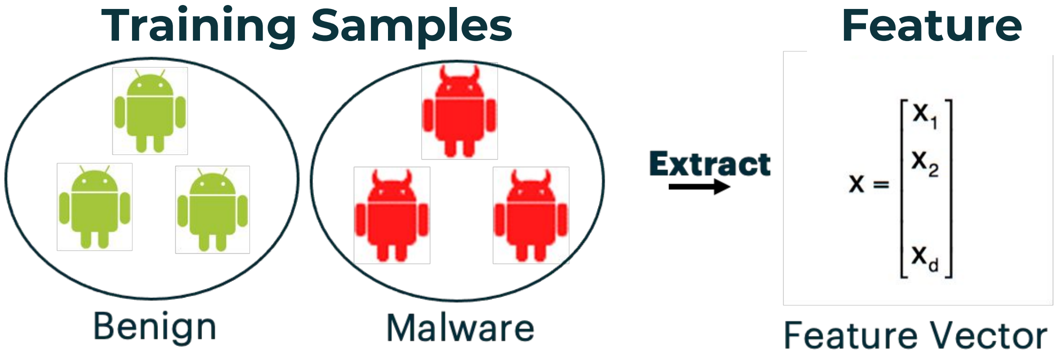

Training Samples

Benign

Malware

Extract

Feature

$$x = \begin{bmatrix} x_1 \\ x_2 \\ \\ x_d \end{bmatrix}$$

Feature Vector

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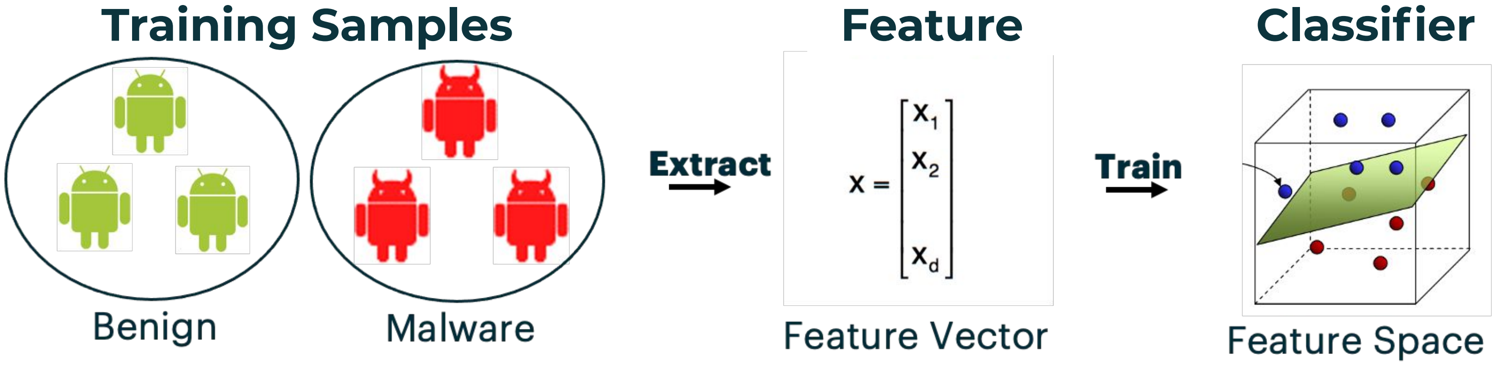

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Feature Vector

Train

Classifier

Feature Space

Issue with Android Malware Detection

- Focus on producing models with high accuracy
    - What about model attackability?

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Attackability of the Model is also Important!

Issue with Android Malware Detection

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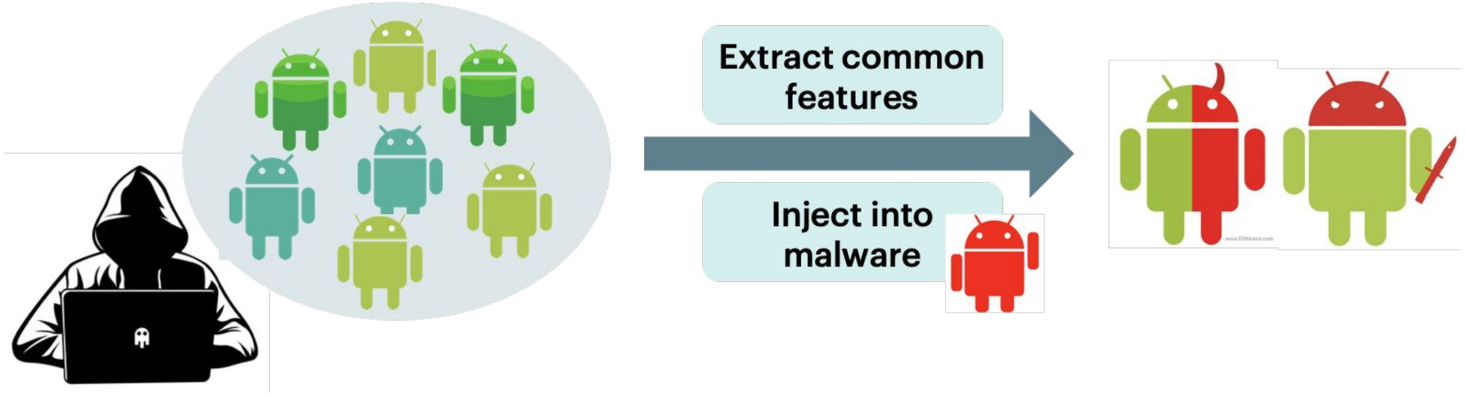
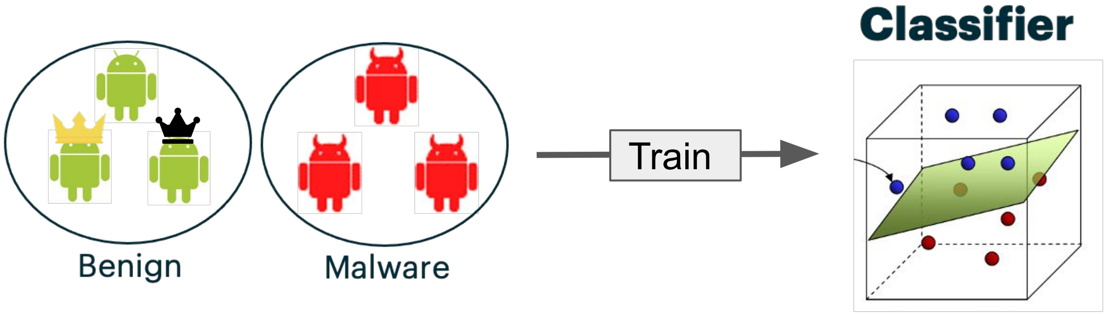
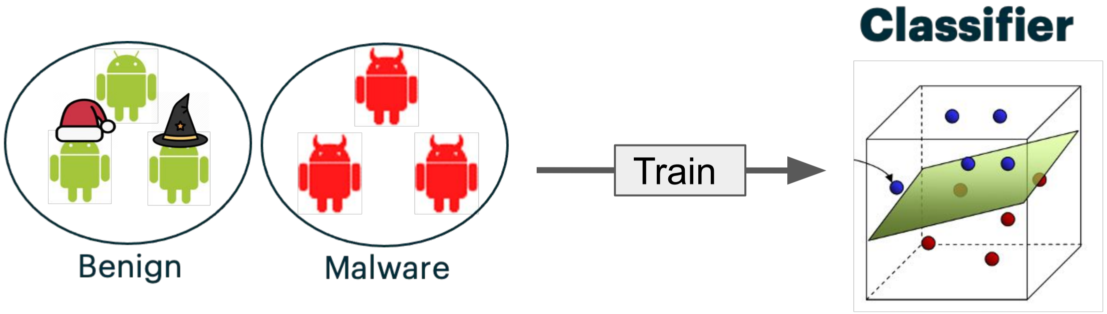
    - What about model attackability?
- Mimicry Attack:
    - Inject features they think represent benign to mislead detection



Issue with Android Malware Detection

- Different sets of benign samples, different impacts on results





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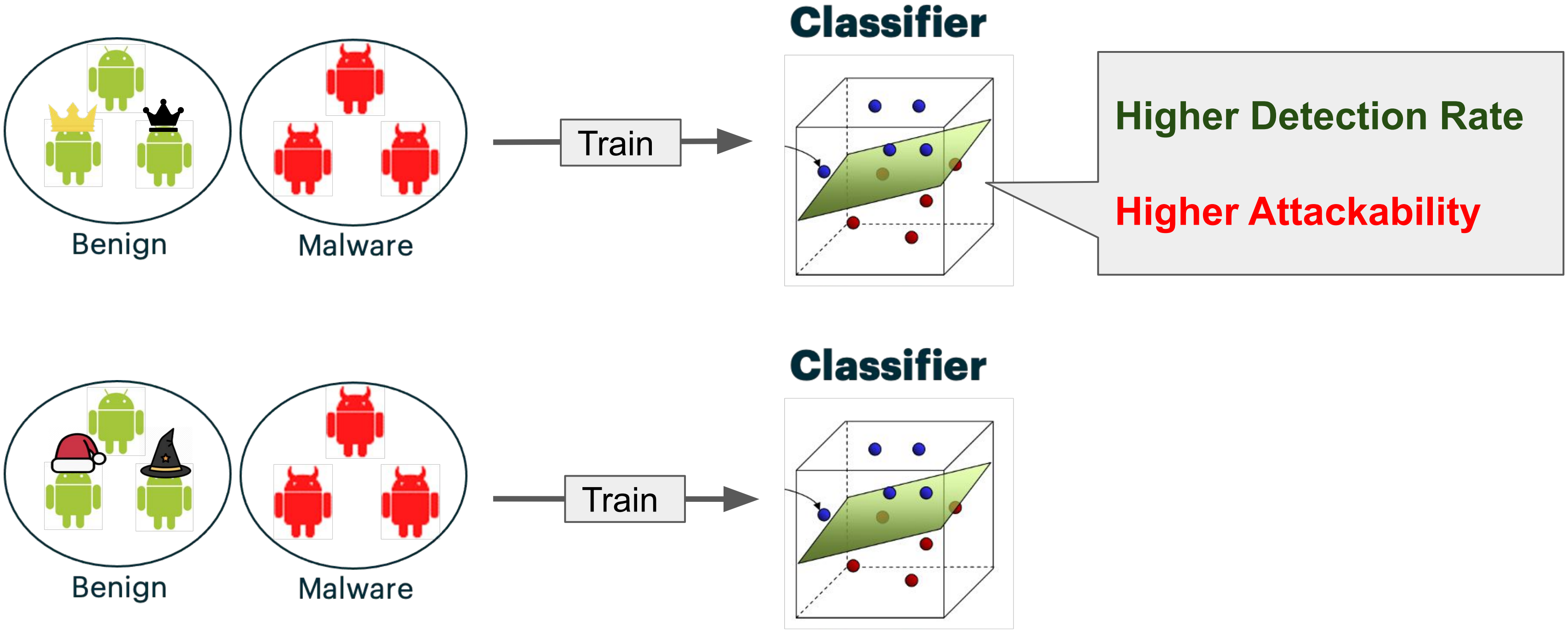

Higher Detection Rate

Higher Attackability

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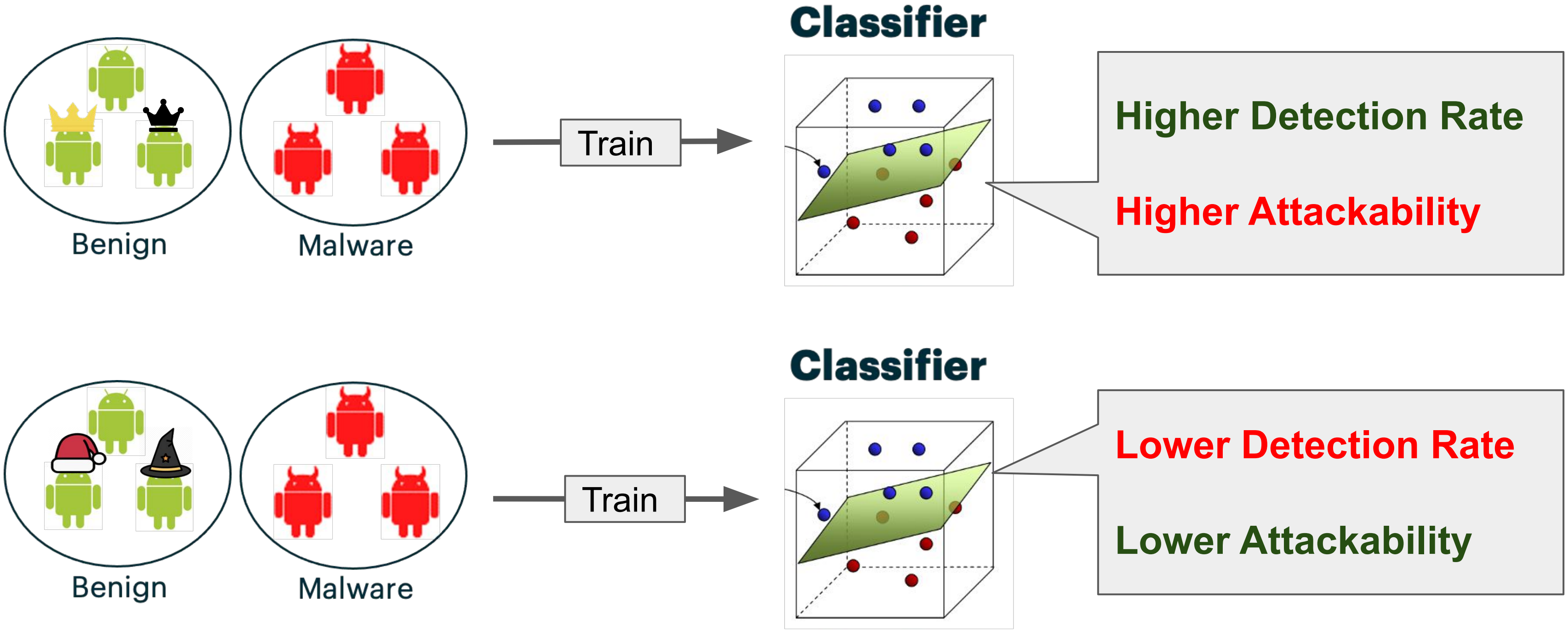

Higher Detection Rate

Higher Attackability

Lower Detection Rate

Lower Attackability

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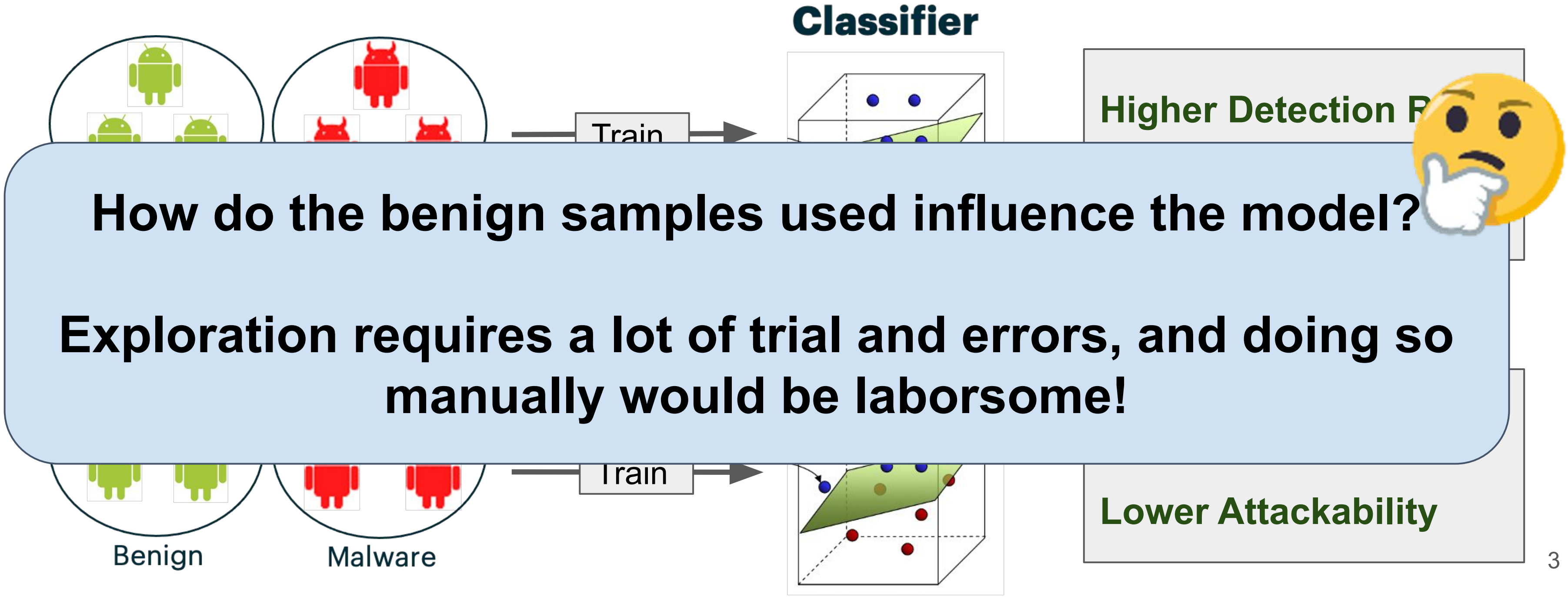

How do the benign samples used influence the model?

Exploration requires a lot of trial and errors, and doing so manually would be laborsome!

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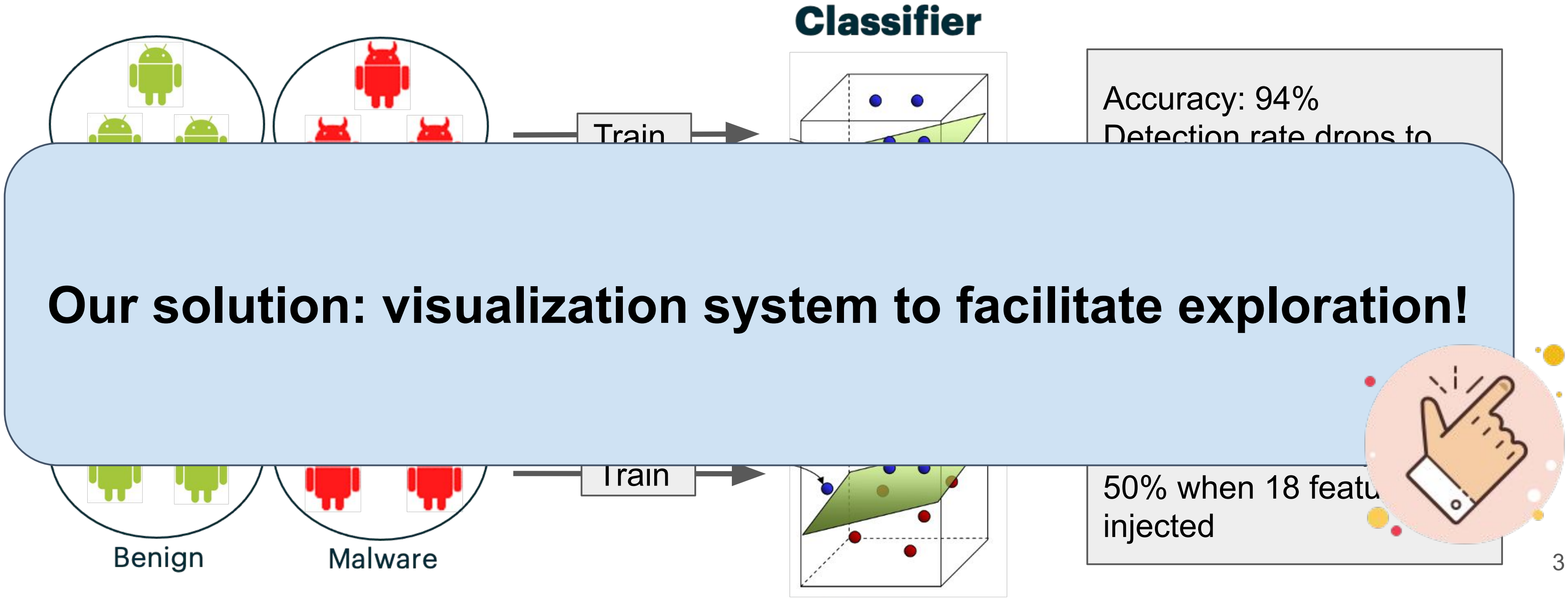
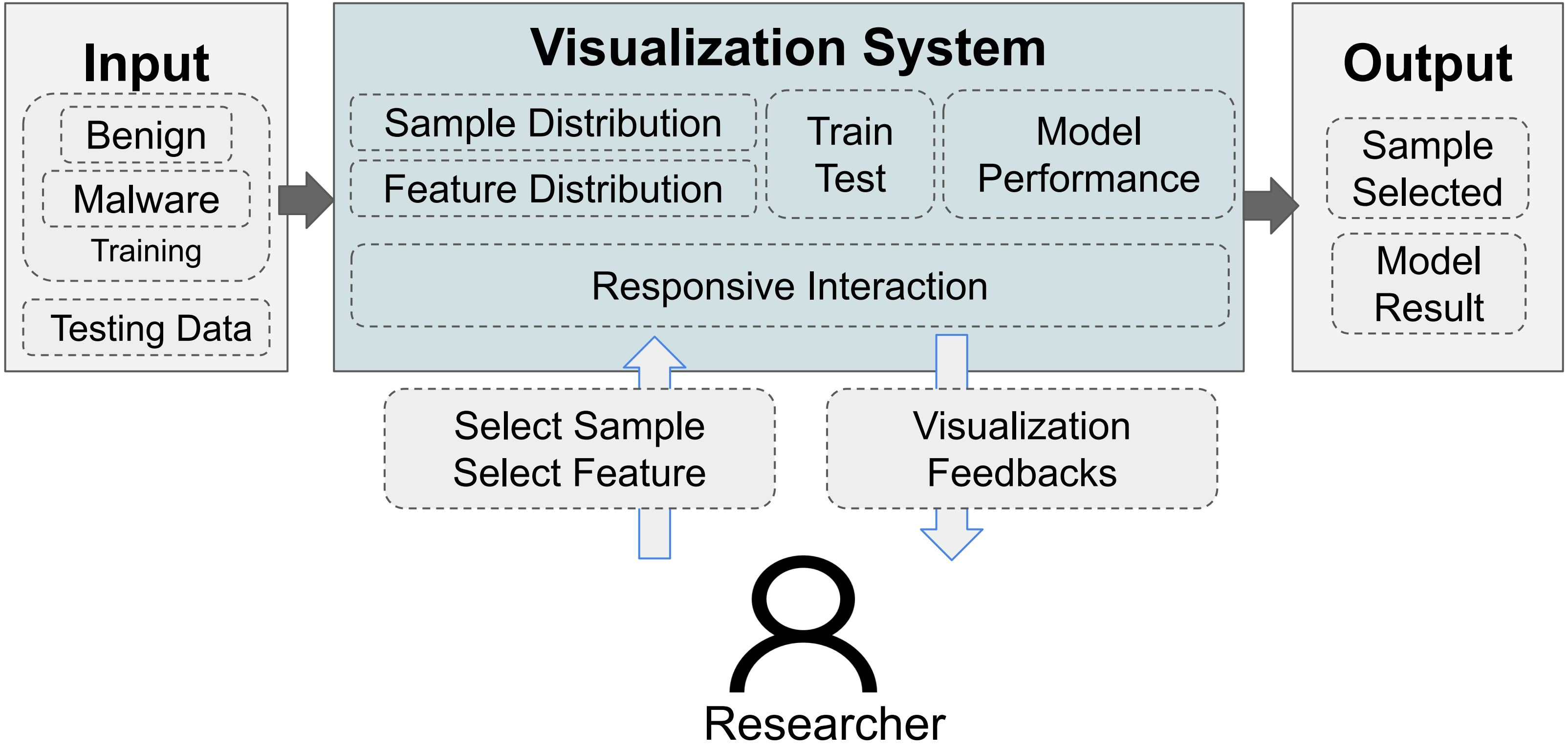


Accuracy: 94%
Detection rate drops to

50% when 18 featu
injected

Our solution: visualization system to facilitate exploration!

High Level Overview



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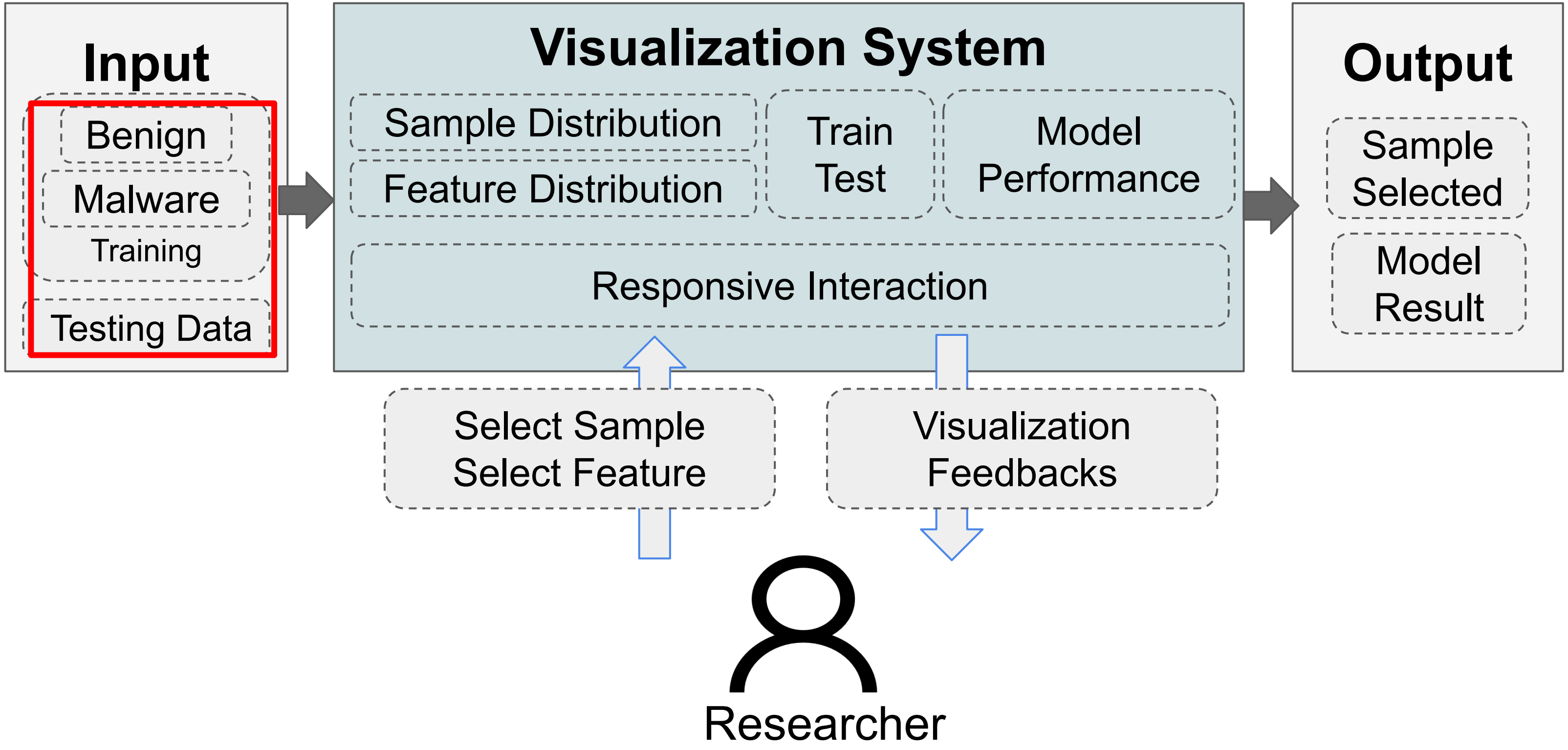

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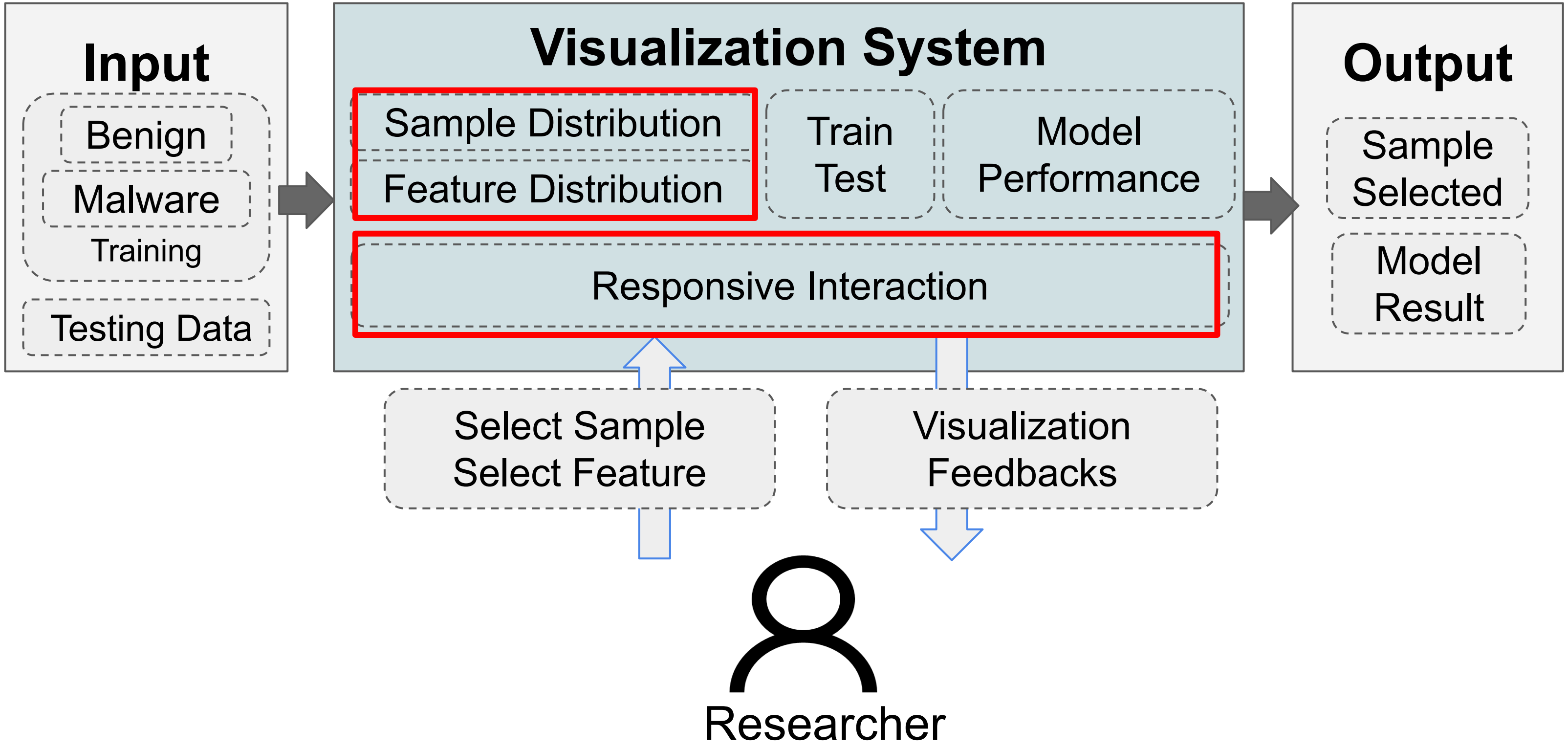

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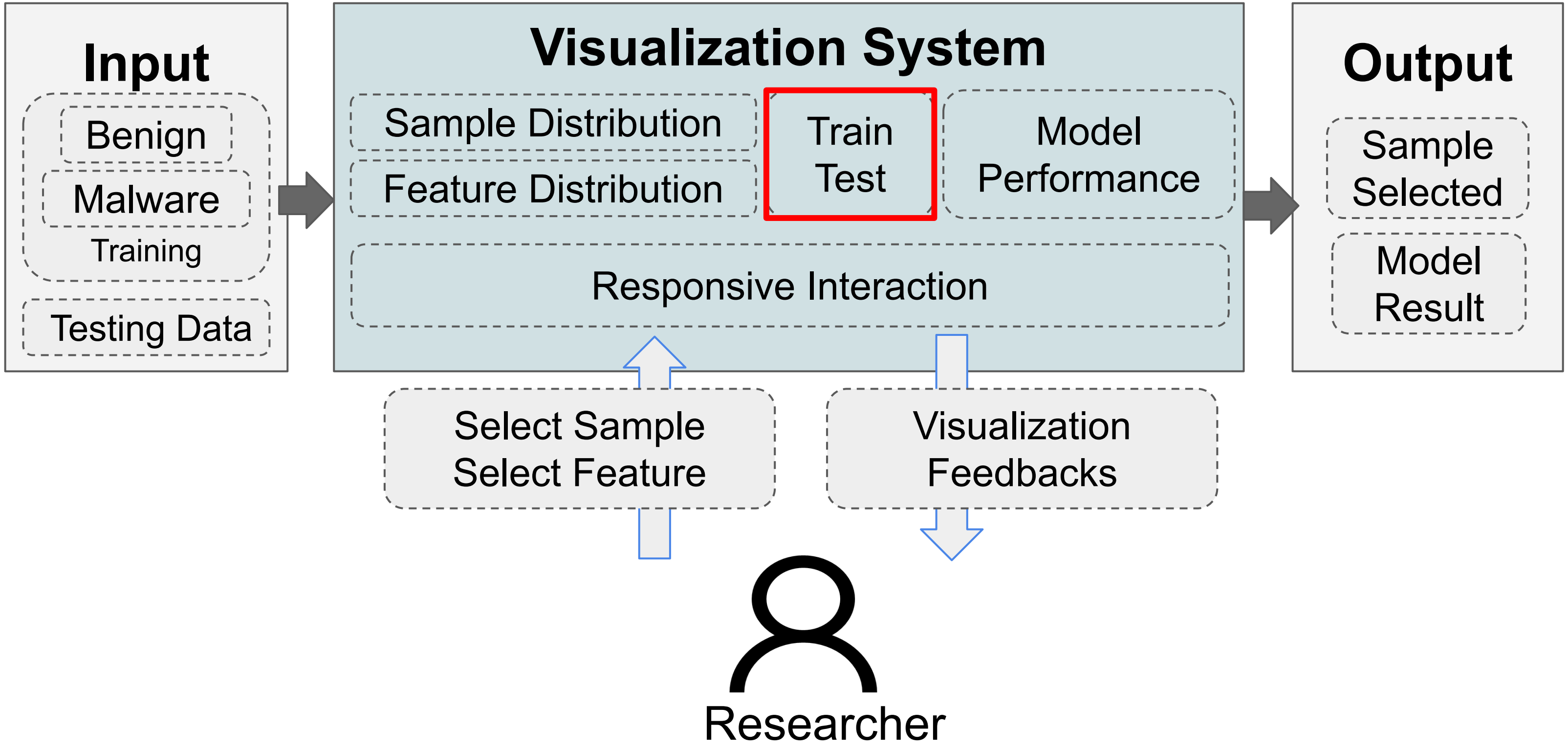

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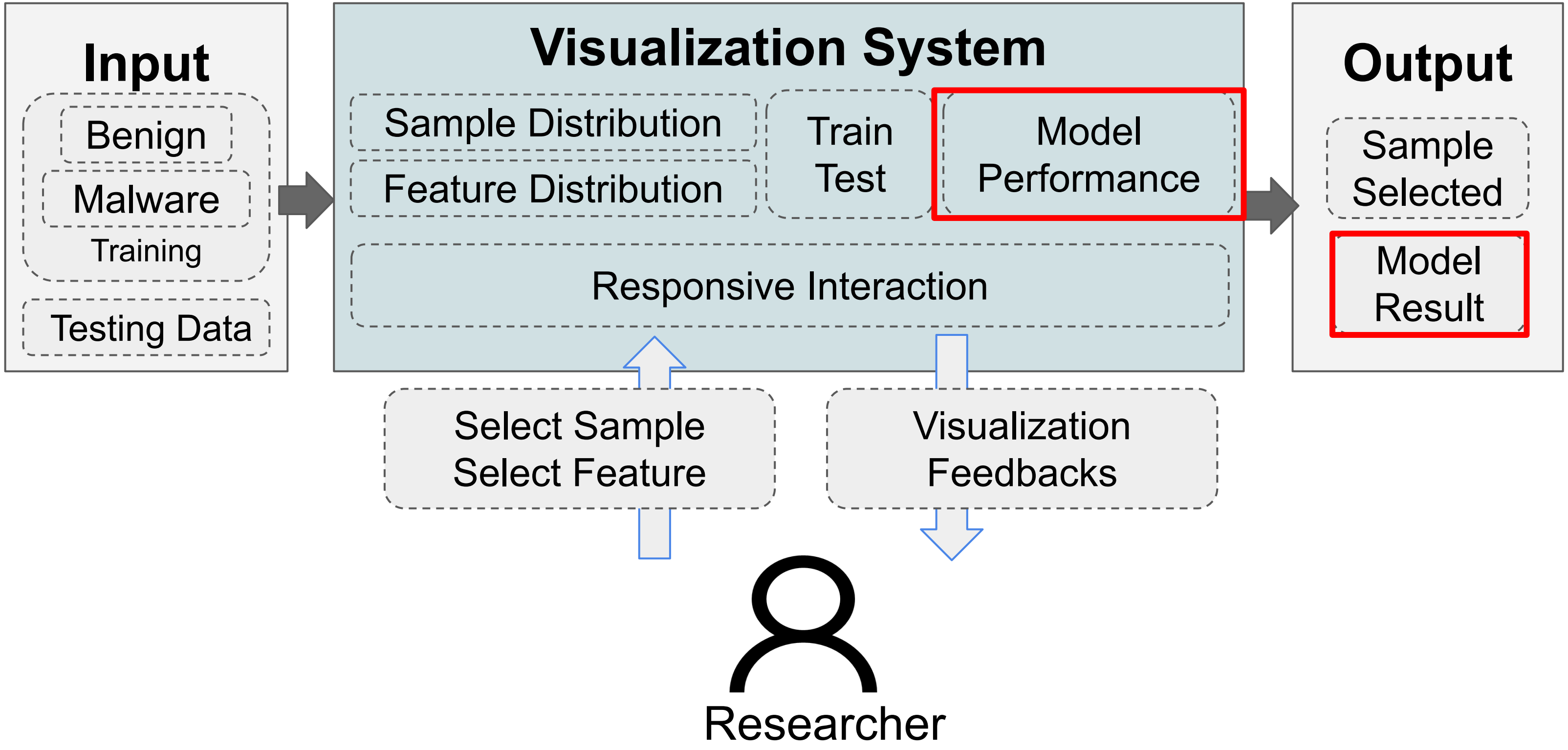

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- Well-known Android malware detection technique [1]
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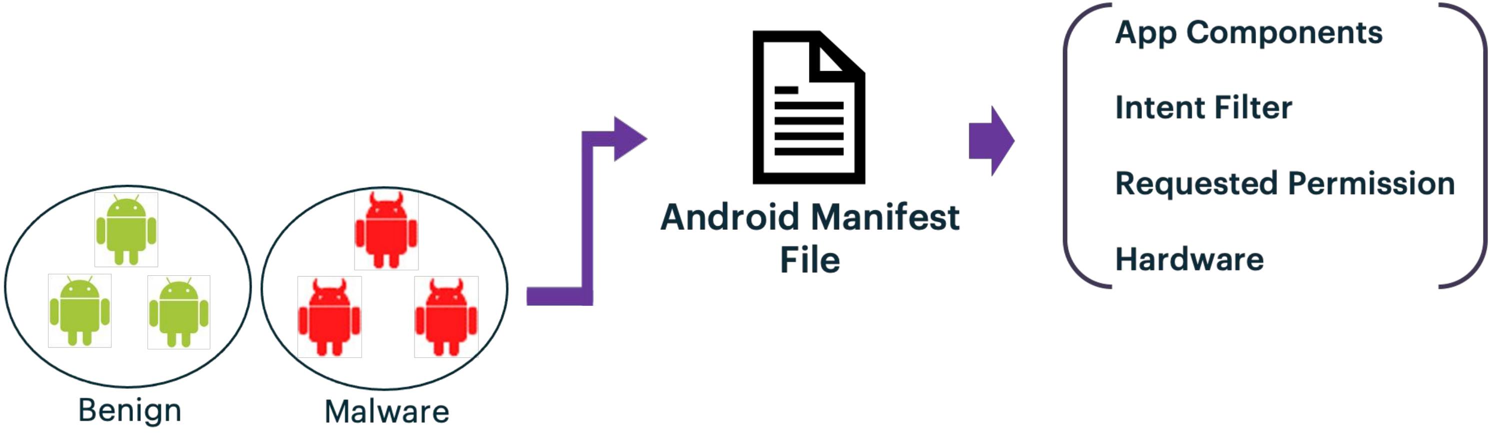

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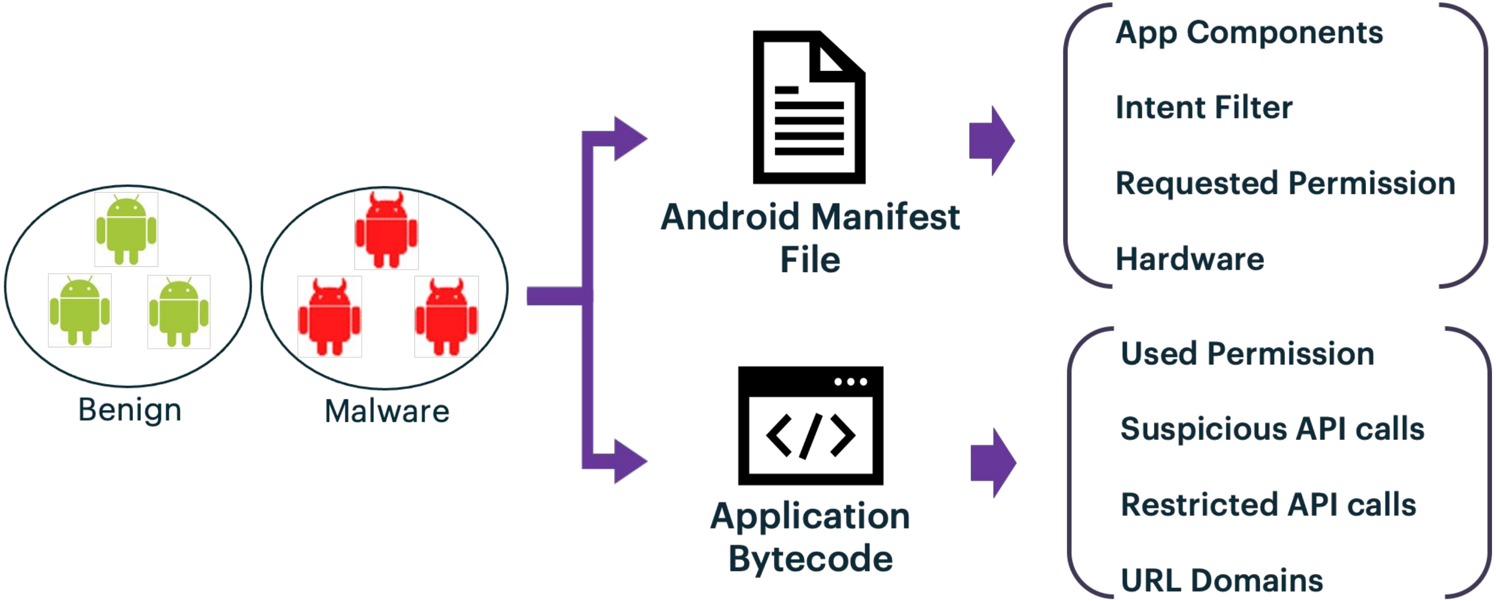
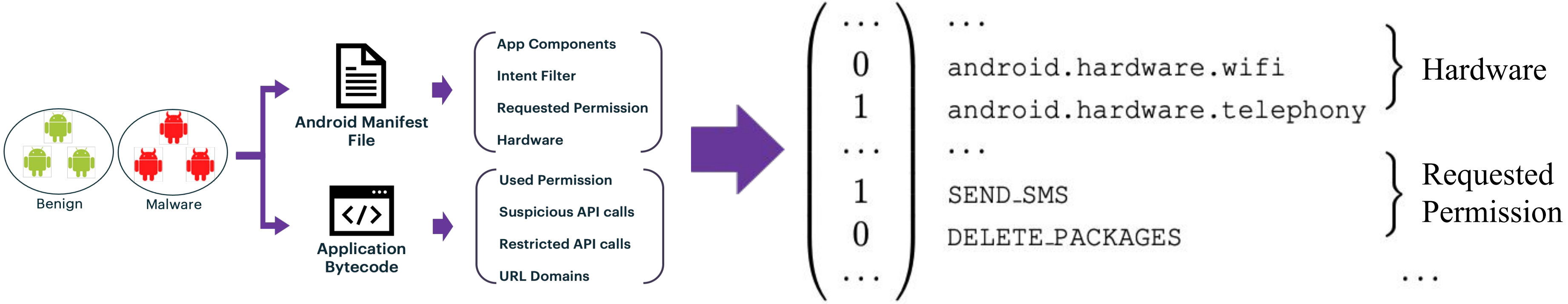


DREBIN: Case Study

- Binary values indicate presence / absence of feature
- Concatenate features from all samples to form feature space
- SVM classifier



Benign

Malware

Android Manifest File

Application Bytecode

App Components

Intent Filter

Requested Permission

Hardware

Used Permission

Suspicious API calls

Restricted API calls

URL Domains

$$\begin{pmatrix} \cdots \\ 0 \\ 1 \\ \cdots \\ 1 \\ 0 \\ \cdots \end{pmatrix}$$

...

android.hardware.wifi

android.hardware.telephony

...

SEND_SMS

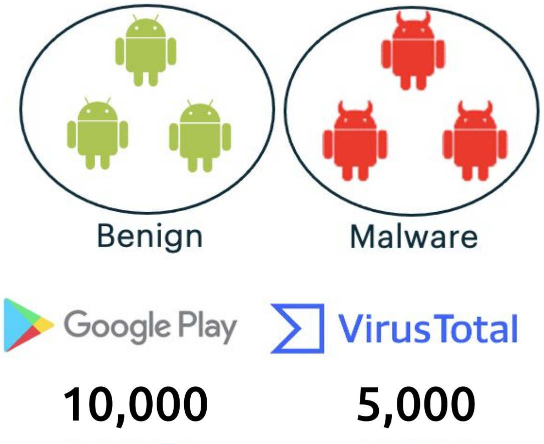
DELETE_PACKAGES

Hardware

Requested Permission

...

Data



Android Sample Data:

- 5,000 malware from VirusTotal
- 10,000 benign from Google Play
- From year 2011 to 2019

Types of Data:

- Android Samples
  - Temporal
  - Drebin Features
- Model
  - Performance
  - Attackability

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- Select particular set of samples and features to train model

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    - Locate misclassified samples
  - Interpret why certain samples being misclassified

Demo

Working scenario of the tool

Limitations

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- Dealing with large feature space
  - Scalability
  - More flexible approaches to select features
  - User has no idea on features for particular samples

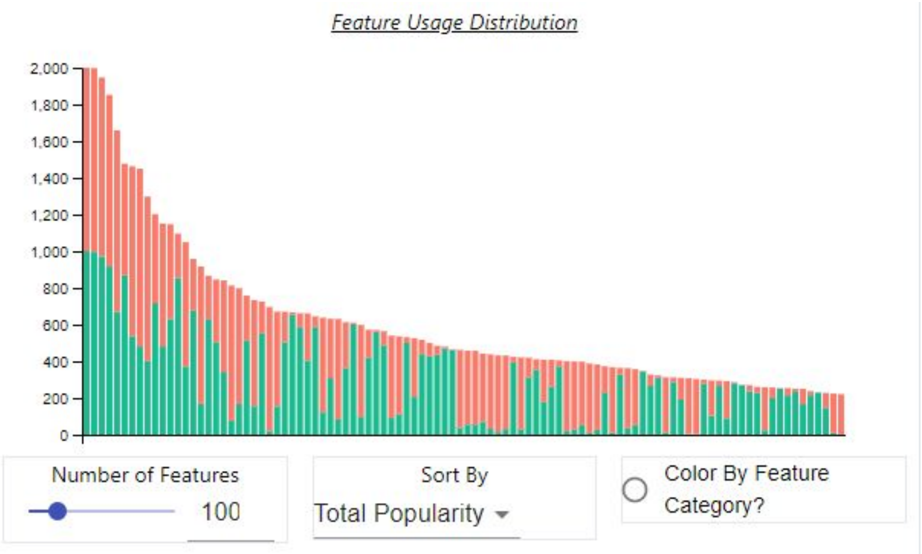
Limitations

- No mechanism for cross experiment comparisons
  - Add juxtaposed view for comparisons
  - Less control over the testing samples

- Few “What-If” functionalities included in the system
  - Allow user to modify / oversample training samples

Lesson Learned

- Prototype, Prototype, Prototype!



Number of Features 100

Sort By Total Popularity ▾

○ Color By Feature Category?

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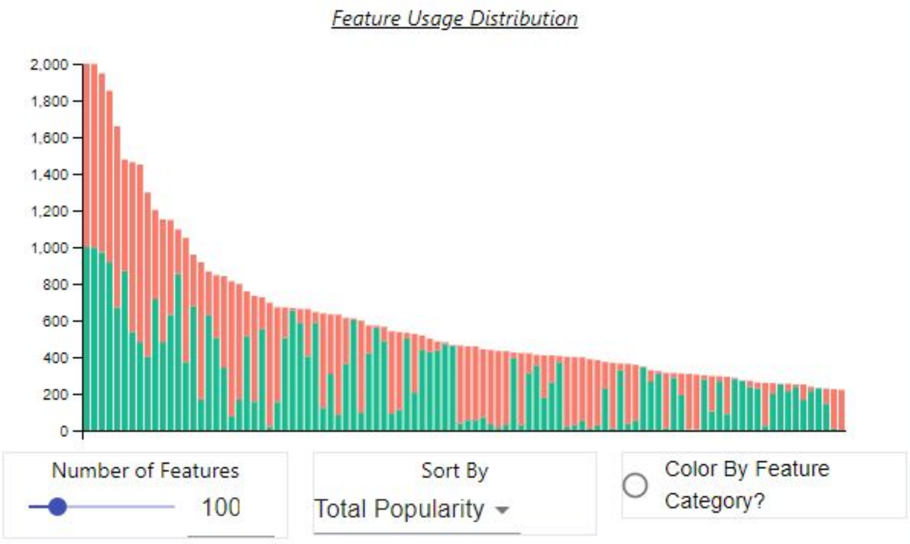

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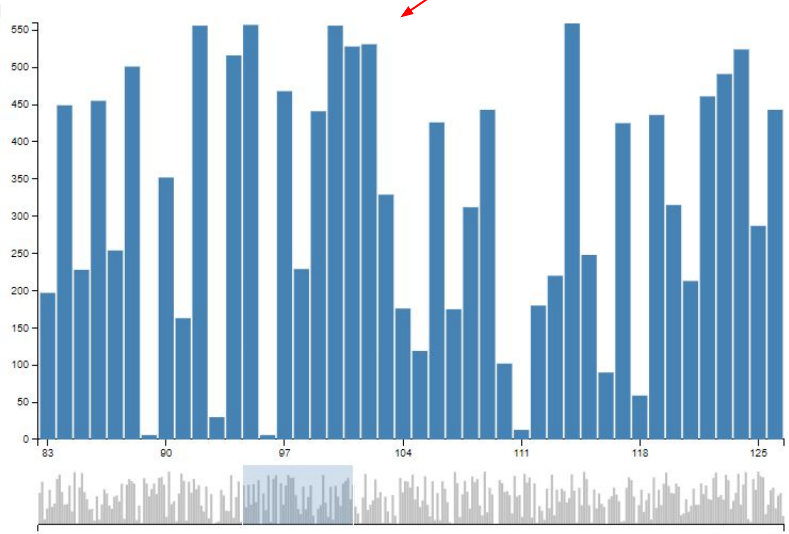
Focus



Context

Thank you! Q&A

Intro & Framing

- Research Topic (a tool to facilitate exploring the relationship between training data and resulting model)?
  - How to select the set of benign samples that results in the best performance?
  - OR
  - Current process of performing such exploratory tasks are time consuming?